BreathIn: A breath pattern sensing approach for user computer interaction

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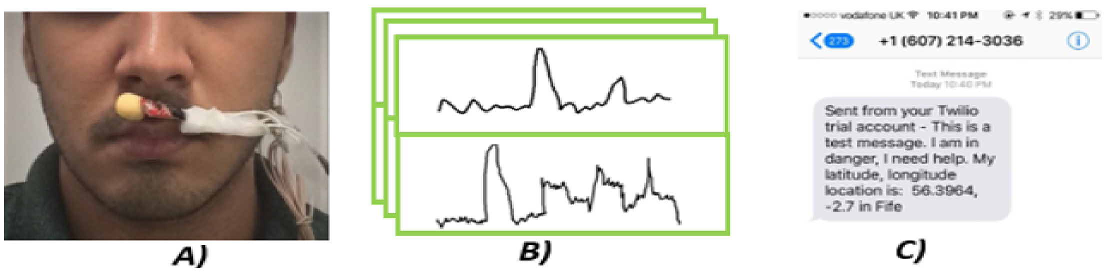

Figure 1: BreathIn MEMS Sensor on mic headpiece (A), Signal with breath event (top), FFT of signal (bottom) for N participants (B), Help message generated with current location (C)

ABSTRACT

New interaction modalities in human computer interaction often explore common sensory inputs including touch, voice, gesture or motion. However, these modalities are not inclusive of the entire population type, and cannot be utilized by a group of people who suffer from any limitation of that sensory input. Here we propose BreathIn: an interface tool for enabling interaction with computer applications by using discreet exhalation patterns. The intent is that such patterns can be issued by anyone who can breathe. Our concept is based on detecting a user's forced exhalation patterns in a time duration using a MEMS microphone placed below the user's nose. We breakdown the signal into FFT components and identify peak frequencies for forced voluntary "breath events" and use that in real-time to distinguish between "exhalation events" and noise. We show two major applications of such an interaction tool: a) adaptation of computer applications using breath, b) using the breath interface as a discreet, emergency signal for prospective victims of crime.

CCS CONCEPTS

• **Human-centered interaction → Human computer interaction**; Interaction techniques;

KEYWORDS

breath; BreathIn; breath sensing; exhale

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1 INTRODUCTION

Breath, a fundamental signature of life, was classically studied from a biological perspective in medical research. It's transitioned slowly to being studied in translational health care applications to identify markers for various health care conditions, to being used as an input in augmentative and alternative communication (AAC) devices or for control input in games, for example.

Breathing patterns consist of a cycle of long or short inhalations and exhalations, which can be both voluntary or involuntary/reflexive in nature. Distinctions between different types of breathing patterns or breath-prints have been used to identify respiratory diseases[12] or markers of stress in participants[2]. Recent studies have demonstrated that people suffering from various diseases such as renal, cancer or asthma, carry distinct biomarkers in their exhalations which could be analyzed using optical spectroscopic techniques[10].

In HCI, breath based control has been used as an interaction medium in gaming where Tennent et al.[9] demonstrate how breath measured through a mask could be used as a one dimensional control in some prototype games.

Classical breath detection techniques have involved a variety of technology and methods. For example, analyzing long exhales from the mouth by breathalysers, or using forced mouth exhales for controlling computer games[9] or in a few cases using "puffs" of breaths from the mouth to control applications on a smart watch [8]. However, these techniques are not discreet [13], as the person

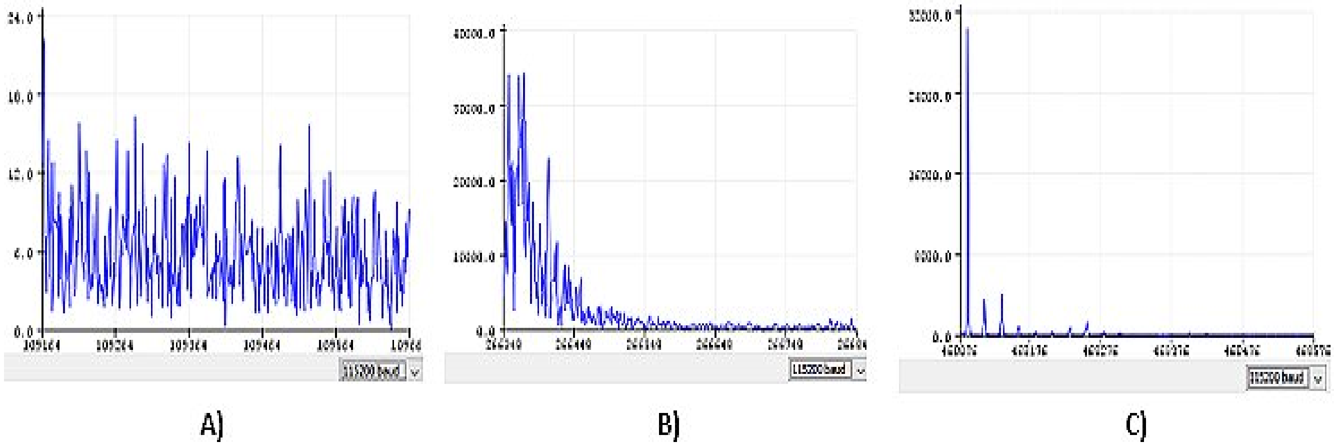

Figure 2: FFT analysis of incoming signal from 1 user from MEMS along a continuous time series (frequency as bins), with the Y axis being the amplitude. A) depicts external noise, B) depicts exhale event, C) depicts human speech

has to physically blow from their mouth in all cases, so instead we propose to analyze subtle nose exhalations to enable interaction.

Our approach makes use of a MEMS microphone (ADMP401) which is placed below the user's nose (Fig 1.A) and interfaced with a Teensy 3.2 to stream data into the computer for analysis. We distinguish the breaths from noise based on FFT component decomposition to identify peak frequencies associated with voluntary exhales. In our first application prototype, we demonstrate how a different number of breaths in a 4 second window could be used to control different things on a computer such as playing/pausing music, changing background, controlling cursor movements. In the second prototype, we demonstrate that when a user exhales in a sequence of breaths an automatic emergency help message with their current location is sent to emergency contacts (Fig 1.C)

2 RELATED WORK

Existing research in HCI has explored breath exhalations for mobile phone interface control as an alternative interaction technology for people with restricted motor movements [3], for biofeedback based breathing enhancement using VR[11], for controlling game interfaces[1]. Vesicular breath patterns have also been known to have sound frequencies, ranging from 60Hz - 600Hz[4], with forced exhales and wheezing sounds ranging from 350-950Hz[7]. This proved to be highly significant in our model design as we mainly focused on identify forced "exhalation patterns" from peak FFT frequencies of the incoming signal.

3 PURPOSE

Here we propose the detection of "exhalation events" using BreathIn for two primary purposes:

a) Using a sequence of "exhalation events" to send a discreet emergency message to the user's emergency contacts with their current latitude and longitude position. A further extension of this is to embed this interface in nose rings/studs to allow the wearer to trigger emergency messages when in danger to ensure personal safety. (Fig 1.A)

b) To facilitate discreet interface adaptations using the number of breath events detected in a given time frame (for example 4 seconds). 1 breath detected -> change background, 2 breaths detected -> play music, 3 breaths detected -> pause music etc.

4 DESIGN AND BREATH STATE DETECTION

The first step was to capture the breath exhalation from the nose. We made use of an ADMP401 MEMS microphone (as shown in Fig 1.x) with a high signal noise ratio, placed below the user's nose to capture the breaths. The MEMS microphone was interfaced with a Teensy 3.2 micro controller so as to stream the analog signals data into the computer. A Fast Fourier transform analysis was then carried out on the incoming signal. The sampling frequency associated with the MEMS was 8 kHz and the number of samples was 1024.

To avoid discontinuities in the real-time periodic time-series signal data, which consists of noise and possible breath events, a forward FFT windowing function was implemented on the real values of incoming data. A hamming window was implemented so as to reduce "ripple effects" and to get data as close to the actual frequency spectrum of the signal. Then, the FFT values were computed using the arduinoFFT library. The amplitude of each component of the FFT was computed by computing the magnitude of each complex FFT value coefficient (by computing the sqrt of the sum of the squares of the real and imaginary part of the FFT value). The spectral analysis using the FFT was then plotted on the serial plotter of the Arduino IDE. The frequencies associated with the highest peaks were then identified for the continual real-time spectrum analysis.

We then used a threshold mechanism over the highest peak frequencies, such that if the most dominant frequency was between 350-800Hz, then that was associated to an exhalation event, otherwise it was classified as "noise".

Furthermore, long and short exhales were determined based on the time duration of how long the dominant frequency was in the 350-800Hz range. If the dominant frequency was in the 350-800Hz

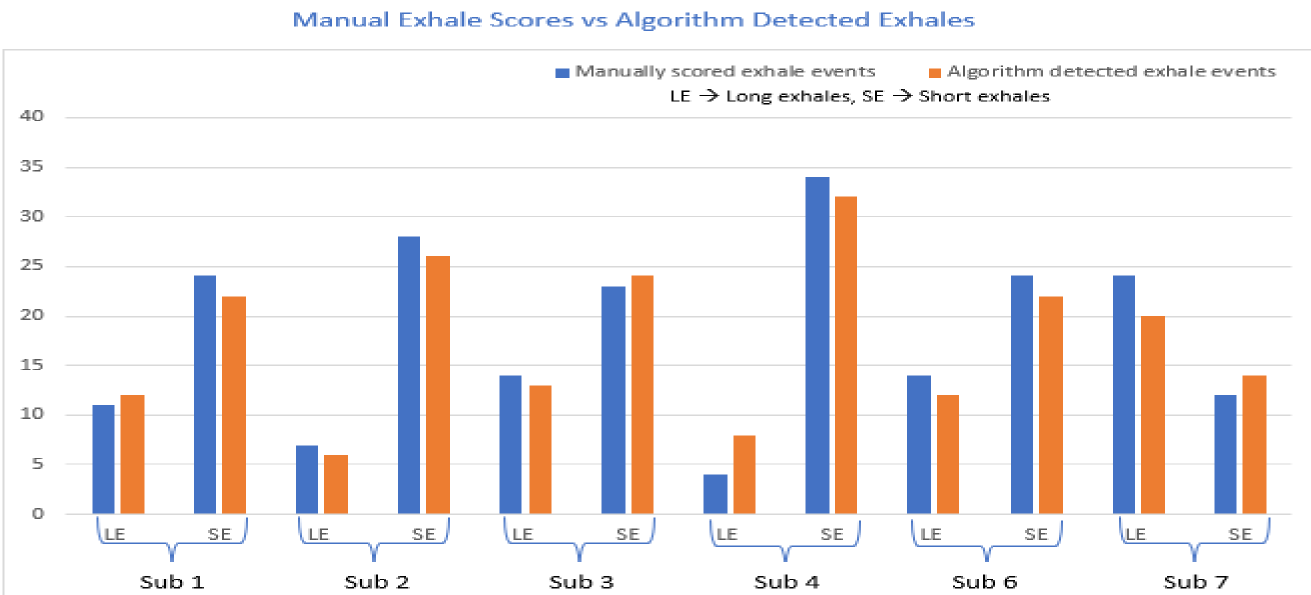

Figure 3: Comparitive analysis of manually scored breath exhale events vs algorithmic detection of exhale events across 6 users

range for >1 second, it was classified as a long exhale or else a short exhale. Fig 2 depicts the FFT of external noise, forced exhales and human voice/sounds. Similarly Fig 4 depicts the dominant frequencies for different event types (noise, forced exhales and human voice/sounds). The blue dots in the figure signify the dominant frequencies human speech, while as the red dots depict the dominant frequencies for forced exhale patterns (usually between 350-850Hz as shown by the plot) in real time streaming. The remainder depicts external noise.

The detected breath events were streamed in Python. Different sequences of events (forced long and short exhales) in a 4 second time window were used to carry out certain manipulations on the computer interface. We made use of the Twilio API to send emergency messages on phones from Python. The emergency messages were sent when a sequence of short, long and short exhalation was detected in 4s window. The emergency help message comprised of a short help text along with the current user's latitude/longitude location (as decoded by the geocoder library in Python).

Other sequences of breath events were employed to enable control of services from Python - a sequence of two short exhales played a mp3 music file while three short exhales paused the music, and a sequence of long and short exhalations carried out background changes on the computer.

5 STUDY AND RESULTS:

Our preliminary study of 6 users (4 males and 2 females, age 18-22) aims to provide an early validation of BreathIn (our breath detection interface system). Each user wore a neckband headset microphone with the MEMS sensor placed on the microphone, just below the user's left nostril (as shown in Fig 1.A).

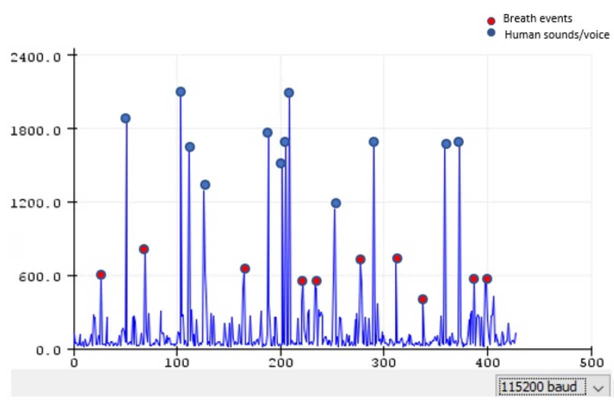

Figure 4: Dominant frequency plot in real time of forced exhale events (red dots), human speech (blue dots) and noise

The data acquired was streamed for analysis purposes in Arduino IDE via Teensy 3.2 micro controller. The real time FFT computed along with the peak (dominant) frequency detection threshold-ed between 350-800Hz was used to identify forced breath exhales of users and to differentiate these from external noise/sound and regular breathing patterns. Each user was exposed to two interfaces for 180 seconds each. The Twilio messaging service interface created in Python and the multiple control interface (comprising of music play, pause and background changes) were to linked to the user's voluntary forced breath exhale events. The number of voluntary breath exhales were also manually scored to determine accuracy of the detection algorithm.

Fig 2 shows the FFT graph plots for three major conditions - exhale events, human speech and noise. The X axis corresponds to

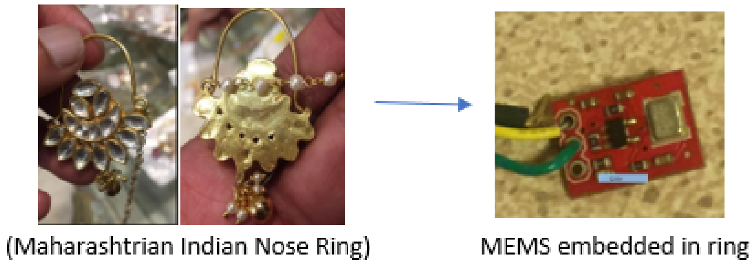

Figure 5: Embedding MEMS sensor in nose rings for personal safety

the frequency bins over a continuous time series while the Y axis corresponds to the strength of the frequency. Similarly, Fig 4 shows the dominant frequency plot for the breath states, external noise and speech where the Y axis corresponds to the current dominant frequency along the X axis time series.

Fig 3 shows comparative bar plots of manually scored forced breath exhales (long and short exhales) vs algorithmically detected forced exhales for each user. The figure shows the accuracy of the interface across the 6 users.

The results in Fig 3 show that our algorithm was able to detect 204 forced breath exhales (true positives) out of 219 exhale events, while the algorithm detected 8 false positives and 15 false negatives respectively. Based on this we computed the algorithms sensitivity = 0.931, precision = 0.962 and the accuracy = 0.8987.

Using such breath exhale events, user interface applications including an emergency message system and music/background control were carried out to depict prospective applications of such a technology. And as noted, adaptations were only shown during the forced exhale breath state.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we proposed theBreathIn: a breath exhale sensing interface system. We bifurcated forced exhale patterns from external noise using a Fourier analysis over the real-time data recorded the ADMP401 MEMS and used those patterns to carry out several interface adaptations, with a possible safety use for emergency messaging for prospective victims of crime. Future work, could involve focusing on developing this interface to be embedded in nose rings/studs (as shown in Fig 5) for A wearer to send a message discretely when in a victim situation. Preliminary analysis major focused on identifying peak frequencies associated with exhale events, however future work would involve a more thorough extraction of exhale features using other algorithms such as RMS, extracting ICA, PCA components to improve the accuracy of the detection algorithm.

This interface prototype is still a work in progress and a more comprehensive evaluation of the interface on a greater number of subjects with the above suggested feature extraction algorithms may yield richer insights. We also hope to further improve the design and ergonomics to realise a more wearable prototype to be used in real-world situations. We envisage such sensors in regular eye-wear for emerging user groups [5], eye-tracking wear [6], VR/AR wear, sports glasses and security glasses.

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